Decision Support System for Airline Operation Control Hub Centre (DiSpAtCH)

Initial research results and developed framework

Jonas Ernst Bernhard Langner, Thomas Feuerle
Institute of Flight Guidance
Technische Universität Braunschweig
Braunschweig, Germany
jonas.langner@tu-braunschweig.de,
t.feuerle@tu-braunschweig.de

Garoe Gonzalez
BGS Research & Rapid Development
Jeppesen GmbH
Neu-Isenburg, Germany
garoe.gonzalez@boeing.com

***Abstract*—If the global air traffic increases again over the next years, it will lead to additional stress on airports, air traffic controllers, and airlines. From an airline perspective, Operation Control Centre (OCC) must prepare them to handle not only more aircraft but also to solve operational disruptions in a much more complex environment than today. Based on research on Artificial Intelligence, Machine Learning, and the state of the art in Airline Operation Control Centre Research, a framework for a decision support tool (DST) is developed. The proposed DST (DiSpAtCH) aims to reduce the time, which is needed to find a feasible solution for a specific disruption situation. Furthermore, the feedback of the DST should increase the situational awareness of the current disruption situation and help the people in charge during the disruption management process within an OCC.**

Keywords – Airline Operation Control Centre; Machine Learning; Situational Awareness; Decision Support Tools

I. INTRODUCTION

The airline industry is an industry with high potentials to get disrupted by many external influences (see Figure 1).

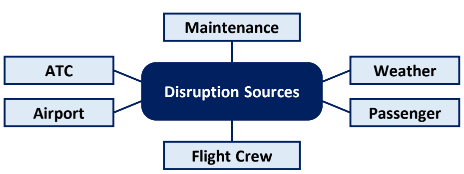

Figure 1 Disruption Sources [1][2]

To counteract disruptions, airlines operate so-called Operation Control Centre. The main tasks of OCCs are to control the operation continuously and aim to identify possible disruptions as soon as possible to initiate actions to reduce the impact or even prevent any consequences at all. Finding a solution for a specific disruption scenario is often difficult since decisions are driven by several factors e.g. cost and available resources. A solution must not only address the obvious disruption, it must also be a feasible solution considering passengers, flight crew, airport, weather, maintenance, and ATC [1][2].

This makes it already a very complex decision-making process. Nevertheless, several forecasts (before COVID-19) showed a probable continuous increase in the total number of flights for the next 20 years [3][4][5][6]. OCCs must therefore, prepare themselves to handle not only more aircraft but also to solve disruptions in a much more complex environment, which makes the disruption management process more difficult [7]. The current situation with a worldwide restart of airline business will allow airlines to implement and use novel and innovative approaches like the one discussed in this paper.

Currently, the operational disruption management process of airlines is typically divided into five steps (see Figure 2).

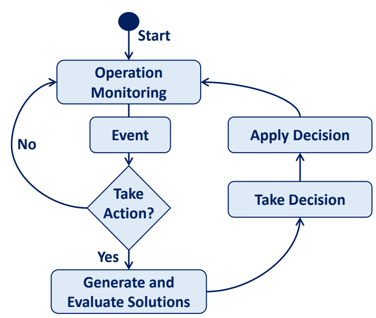

Figure 2 Disruption Management Process [8]

During the phase of operation monitoring all flights are monitored to identify any deviation from the plan. As soon as an event happens, the situation is assessed and a decision for further action is taken. If no action is required, the operation monitoring continues again as normal. In case the event causes any disruptions, solutions are generated and evaluated to restore the initial plan. This step is often supported by computer tools and carried out by experienced controllers. To find the right action for a specific disruption can be challenging

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due to several restrictions that need to be considered (e.g. crew availability or airport resources) throughout the process (see Figure 3). After the decision was taken the action is applied to get back to the step of monitoring the operations [1][8].

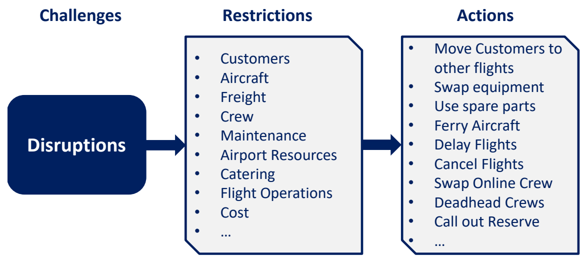

Figure 3 Decision Making Modell [1]

If the disruption management process of airlines will get more challenging and complex in the future, more sophisticated computer tools are needed. Today, disruptions already cost the aviation industry billions of dollars annually [9]. Airlines therefore would benefit from a DST during the step of “generation and evaluation of solutions” and “take decision”. With more advanced algorithms (e.g. machine learning) and more data that is available in a digital format in the aerospace sector the need for a new approach of data-based decision support tools during the decision making process is growing.

Machine Learning (ML) algorithms can provide insights in patterns and structures within datasets. Furthermore, by using labelled data they learn to predict specific behaviours or events. The advantage of this completely data-driven approach is that it is not biased by individual experiences of humans and can therefore achieve more accurate results in many cases [10].

Summarized, the objective of the DiSpAtCH (Decision Support System for Airline Operation Control Hub Centre) project is to elaborate on machine learning and artificial intelligence technologies and how these technologies could efficiently support decision making in an Airline Operation Control Hub Centre in unexpected or very complex situations. Airlines like Lufthansa and Swiss already started to work with Google to research on a very similar topic [13].

II. RESEARCH METHODOLOGY

This chapter describes the applied research methodology shown in Figure 4 and gives an overview of the status of the project. The research methodology is divided into three main phases and each phase consists of two tasks.

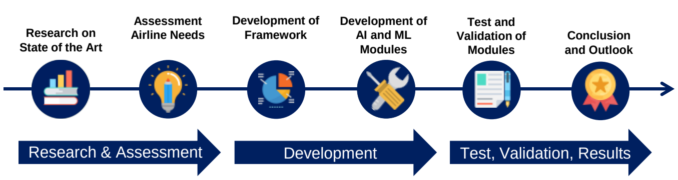

Figure 4 Research Methodology for DiSpAtCH

In the first phase “Research & Assessment” the main goal is to research the current state of the art in the area of machine learning, airline operation and decision support tools as well as to assess the airline needs regarding support during the disruption management process. A comprehensive literature review and several interviews with people in charge of OCCs were carried out. In the second phase “Development” a framework for a new decision support approach is developed. Furthermore, several algorithms are trained and modules for the DST are created. The final phase “Test, Validation, Results” consists of tests and validations of the developed modules and the overall DST. Finally, a conclusion and outlook will summarize the main achievements of DiSpAtCH as well as the impact on the disruption management process from an airline perspective.

Currently the first three tasks of the research methodology already started. A framework was also developed based on the first research and interviews with airlines. The following chapter summarizes the airline needs and provides a set of hypotheses regarding the DST.

III. RESEARCH RESULTS AND ASSESSMENT

Several OCCs have been visited (1 holiday carrier and 4 legacy carrier) to not only identify the state of the art, but also to ask people in charge of disruption management about their needs.

Based on the visits and the interviews of people in charge, three main needs were identified:

- Ability to analyse the current disruption situation and the restrictions regarding the available resources → enhance situational awareness
- Automated generation of disruption solutions regarding the current disruption situation considering the restrictions
- Comparison of disruption solutions regarding their overall costs and time impact on the operation

Furthermore, based on the insights and the feedback during the interviews five hypotheses were defined which should be verified at the end of the DiSpAtCH project. The hypotheses (H) are the following:

H1: The DST contributes to increased situational awareness during disruption situations.

H2: The DST helps to reduce the needed time to find feasible solutions for specific disruption situations.

H3: The DST helps to find solutions that minimize the time impact on the overall operation.

H4: The DST ensures that the costs of actions to counterpart disruptions are decreased in comparison to today’s airline disruption costs.

H5: The DST enables to solve disruptions with fewer resources.

To increase the acceptance of a new DST several interview partners emphasised the importance of the comprehensibility of the results proposed by the DST. Therefore, during the development of the framework the implementation of an optimiser was avoided. The focus is more on situational awareness and an overview of decisions in past similar situations. This should help to increase the acceptance of the developed DST described in the following chapter.

IV. DiSpAtCH Framework

Based on literature research on Artificial Intelligence, Machine Learning, and the state of the art in Airline Operation Control Centre, a framework for the DST was developed. The proposed DST should be able to prove the defined hypotheses.

Regarding the available algorithms to analyse past disruptions and related decisions, several ML algorithms are identified and considered in this research. The following Figure 5 gives an overview of some commonly used machine learning algorithms in the aerospace sector [10][11][12].

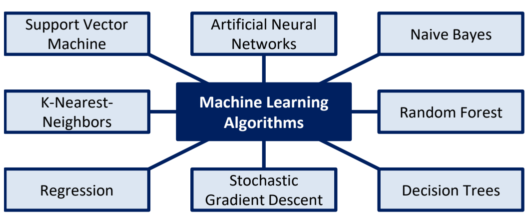

Figure 5 Overview of machine learning algorithms [10][11][12]

Since there is no need to use the same algorithm for each ML module, the algorithm with the best performance can be selected individually for each ML module.

The DiSpAtCH framework shown in Figure 7 is divided in two levels of the DST, the "Basic" and the "Enhanced" version. The basic decision support tool contains mainly the developed process without any ML or AI modules integrated. Only after completion of the basic DST the development of the enhanced DST can start. Both levels are defined as follows:

<u>Basic Decision Support Tool:</u>

Step 1: The preferred solution is selected by using a graphical user interface.

Step 2: The DST is using the information on the current availability of resources as well as the current information about disruptions and the input provided in step 1. The main goal of step 2 is to check if the selected solution is feasible regarding the resources and the current restrictions. If the selected solution is violating any restriction, a conflict warning is immediately shown to the user.

Step 3: If the selected solution is feasible, an estimation of the expected cost and time impact is carried out based on average cost and time values and shown to the user.

<u>Enhanced Decision Support Tool:</u>

Before Step 1: Use of past operational data and AI & ML algorithms to identify disruptions even before they occur or their impact on cost and time is already huge. Based on a database with taken decisions in past disruption situations an AI & ML algorithms is used to propose the top 3 most probable solutions to solve a specific disruption.

Step 3: Based on a database with past values for cost and time impact, disruption causes, and current real prices (e.g. fuel cost) an AI & ML algorithms is used to estimate the precise cost and time impact of that selected solution.

V. Summary & Next Steps

With the described vision of the DiSpAtCH framework the next steps are to start the development and to think about the implementation of a graphical user interface as well as the development and integration of several AI & ML modules.

In general the described framework needs some real-time input data and databases with historical data sets to generate the desired output to help the people in charge during the disruption management process within an OCC.

Real-time data is needed to identify the current disruption situation and restrictions (e.g. available crew/aircraft or weather situation). With the real-time data the basic DST can already be developed. To reach the enhanced level of the DST historical data is needed to train the AI & ML algorithms.

Since it is very unlikely to get access to all needed data from an airline, the development of an airline simulation tool already started (see Figure 6). This tool is in the early stages but once it is finished, it will provide sufficient data to implement and test the proposed framework.

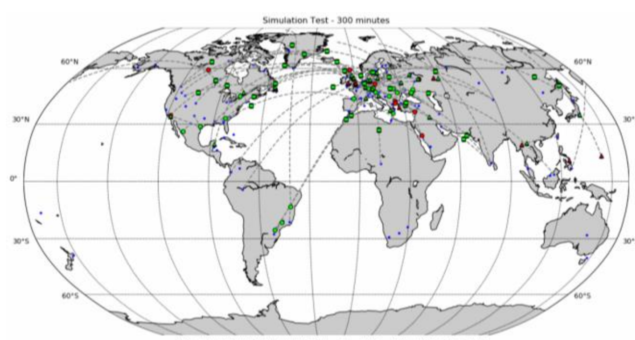

Figure 6 Airline Simulation Tool

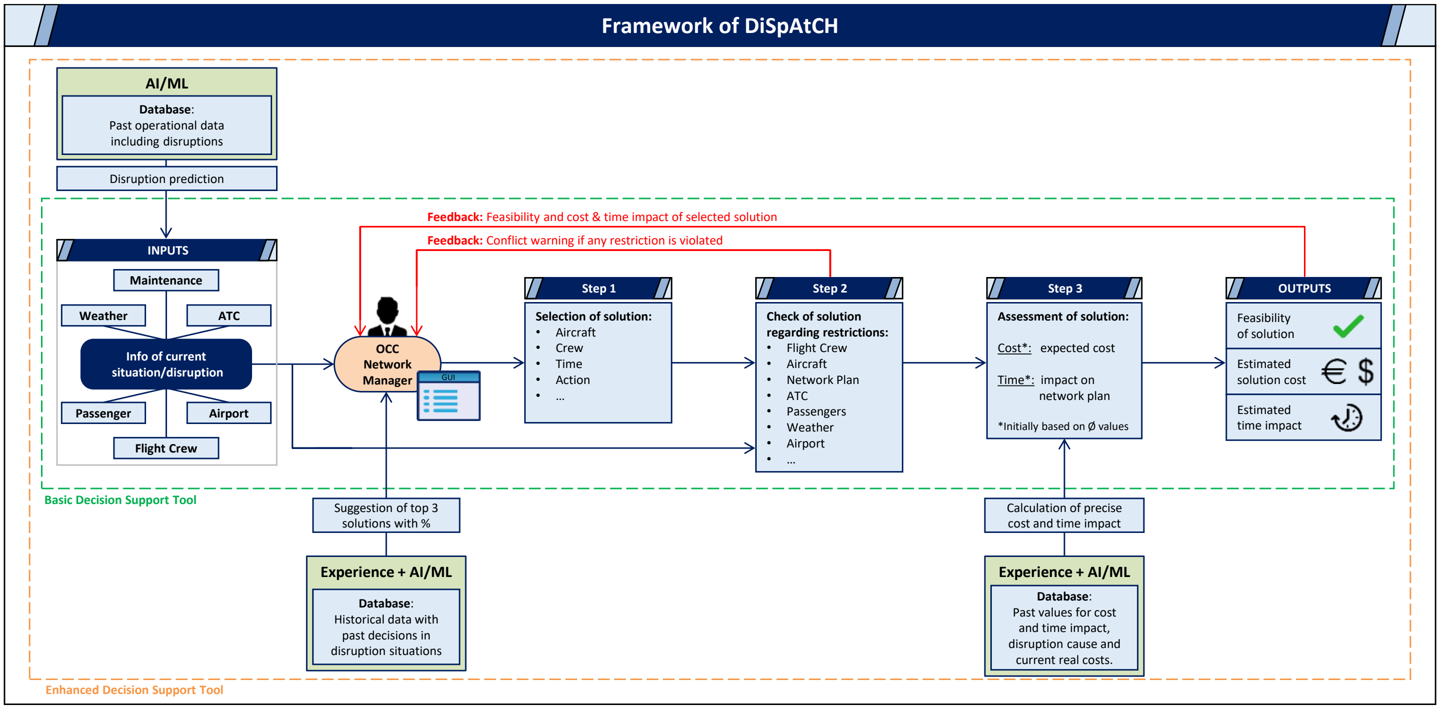

Figure 7 Framework of DiSpAtCH

Besides that, first ideas for the generation of a set of use cases (disruption situations) which will be used to test and validate the DST are already created.

Finally, the DST will be examined along the five hypotheses and an assessment of their achievement will be carried out.

VI. DISCLAIMER

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